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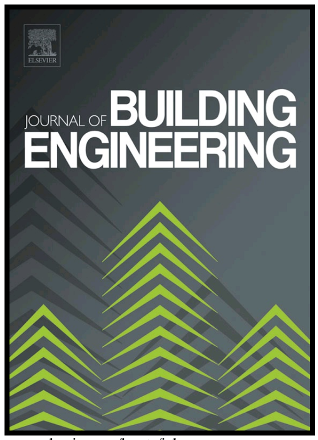

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Classification and Energy Analysis of Bank Building Stock: A Case Study in Curitiba, Brazil

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Abstract

An engineering bottom-up technique has been selected for classification and energy analysis of 72 bank branches in the Brazilian city of Curitiba. A multi-stage approach has been adopted in this study to collect and analyse the dataset of these bank branches, virtually survey and map geometrical and design parameters of the branches and classify them according to shapes, sizes, geographical layout, and construction age. Four types (Type A to D) of bank branches have been identified. Type A branches have the greatest mean conditioned floor area (over 100 m^2) with largest deviation of energy use intensity (over 47 kWh/m^2year). Type B branches are most commonly found in densely populated downtown area. However, over 61% of the branches belong to Type C and D, which are mostly located in less congested sub-urban areas. The study also shows that post-2010s branches are among the largest energy consumers. An in-depth parametric assessment on specific design details from architectural drawings of selected branches was further conducted to identify the effects of building parameters on energy consumption of the bank branches. Despite the minute correlation obtained between energy consumption and design variables (R^2 of 0.253), a Linear Discriminant Analysis suggests that percentage of openings and occupant density are among the defining parameters of a low and medium-high consumer as regards bank branches in Brazil.

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This study provides insights into a better understanding of the design characteristics of bank branches in Curitiba and parameters potentially affecting their energy consumption. The archetype bottom-up technique presented in this study that involved studies at different stages can also be used to define typologies for other types of buildings. This study shows how complex building stock, such as, bank buildings could be classified and their energy performance collectively analysed using multi-stage approach. The approach combined a range of methods, which had been conducted in sequence, such as, virtual survey, building classification, further in-depth parametric and energy assessments of selected bank branches based on architectural drawings using Multiple Regression Analysis and Linear Discriminant Analysis. Such approach enables critical design parameters to be determined in the absence of complete set of building data, which could be adopted for other similar types of complex building stock.

Keywords: building typology, classification, energy benchmarking, bottom-up approach, archetype technique, energy use intensity.

1. Introduction

Buildings contribute to the majority of greenhouse gas emissions globally, with up to one third of the carbon emissions in the United States (US) (DOE, 2012) or more than 38% in the European Union (EU) (Eurostat, 2015) coming from the building sector. Governments around the world have committed to reducing carbon emissions especially from the building sector, with more stringent legislation in place to increase building energy efficiency. More recently, the Paris Agreement has been ratified by 175 parties within the United Nations Framework Convention on Climate Change, with the aim of keeping a global temperature rise well below 2ºC above pre-industrial levels in this century (UNFCCC, 2017). Drastic changes in governments' policies are required to tackle climate change issues, including the use of renewables and more energy efficient measures in the building sector. Despite introduced since early 1990s, studies show only 35% accuracy of energy performance certification systems in Europe (BPIE, 2010) and calculated energy rating often overestimates the energy demand of buildings when compared to measured data (Ballarini and Corrado, 2009).

In Brazil, buildings accounted for 50% of the total electricity consumption in 2014 (MME, 2015). As most part of the Brazilian territory is located within either tropical or sub-tropical climatic zones, these regions are cooling dominant while artificial heating is almost non-existent. According to the National Energy Plan 2030, energy consumption in the building sector is projected to grow 3.7% per year by 2030 (Veloso et al., 2017). In public and commercial buildings, electricity wastage occurs mostly due to inefficient building construction materials and service equipment (Lamberts, 1996). Since the introduction of Law No 10.295 (Diário Oficial da República Federativa do Brasil, 2001) in 2001, Brazil's National Electricity Conservation Programme (PROCEL) has been strengthened and in 2003 the PROCEL Edifica Programme was launched by the Brazilian government with the aim of reducing building energy consumption. Subsequently, voluntary requirements for energy efficiency labelling were introduced to classify buildings according to their energy efficiency level to limit and control energy consumption in buildings (Lamberts et al., 2006). The Energy Efficiency Rating - Technical Quality Regulations for Commercial, Service and Public Buildings (RTQ-C) was published in 2009 to reduce building energy consumption. The RTQ-C produces energy ratings based on the assessment of parameters and specifications taken from three main categories (building envelope, artificial lighting and air conditioning system). A recent study provides a summary of difficulties and weaknesses of the calculation methodology, scope and labelling of the RTQ-C, and identified areas for further studies (Wong and Kruger, 2017).

2. Background and Overview

In the building sector, office and commercial buildings are among the highest energy consumers due to the diversity and complexity of end-user systems and services provided (Jing et al., 2017; Ward, 2008). Key determinants of energy consumption are heating, ventilation and air-conditioning (HVAC) systems, office equipment and computers, lighting types and other energy-related equipment (CBECS, 2015; Jing et al., 2017). Among all, HVAC systems are the main end-users in office buildings, ranging from 48% (US) to 56% (Singapore), followed by artificial lighting (Jing et al., 2017). There has been an increase of 14% in the number of commercial buildings in the US (CBECS, 2015) and a high percentage of office buildings in Asian cities (Lee and Chen, 2008), leading to higher energy consumption.

Among all different types of office buildings, bank buildings consume most energy with average consumption of 301 kWh/m^2 in the US and 48% of the final energy consumption in Greece due to the use of HVAC systems (Spyropoulos and Balaras, 2011). In Brazil, HVAC systems have to be operated in commercial buildings for most of the year except for winter months in a few regions with subtropical climate. Bank buildings are one of the largest commercial building stock in urban areas in Brazil due to their widespread presence across the urban areas. Their electricity consumption accounts for up to 86% of the total energy consumption due to high usage of lighting and air-conditioning systems (Paixão, 2013). Paixão (2013) developed a prototype computer simulation model of bank branch based on 33 key variables identified and gathered from 34 bank branches in Brazil. Borgstein and Lamberts (2014) proposed a methodology for developing benchmark for 1890 bank buildings in Brazil in 57 different climates. Using both statistical and energy audit data, the authors benchmarked end-use energy consumption for bank buildings, including those in Curitiba and validated using thermal simulation (Borgstein and Lamberts, 2014).

2.1 Approaches and methods used for energy benchmarking

To reduce energy consumption in the building sector, it is essential to understand how energy is consumed in this sector. The process of determining how energy efficient a set of buildings are is called energy benchmarking, which involves building classification with energy analysis. A benchmarking system can be developed from a sample of reference buildings (Chung, 2011). In the United Kingdom (UK), an Energy Consumption Guide for office buildings was published in early 2000 to provide benchmarks for typical and good practice energy consumption patterns in office buildings (CIBSE, 2003). Another example of energy benchmarking are energy rating calculation models used in most countries, particularly, energy rating systems developed under Energy Performance of Building Directives (EPBD) in the EU (Katafygiotou and Serghides, 2014). Reviews show various benchmarking methods and their associated benefits and limitations, which can be classified according to 1) public and internal benchmarking (Chung, 2011), 2) white box, gray box and black box methods (Li et al., 2014; Sousa and Jones, 2017), 3) point-based rating systems, hierarchal and end-use metrics, statistical approaches, and simulation model-based approaches (Gao and Malkawi, 2014), 4) engineering calculations, simulation, statistical methods, and machine learning (Borgstein et al., 2016). A Bayesian approach had also been used to develop energy analysis models for non-domestic buildings in London (Choudhary, 2012). However, benchmarking methods are most commonly grouped into top-down and bottom-up approaches shown in Table 1, depending on the reliability and quality of data available (Foliente and Seo, 2012) or based on the granularity or level of detail of the data used (Hong et al., 2013). Low granularity of the information involved in benchmarking energy consumption and accuracy of the methods used to evaluate energy efficiency of buildings are reported to be the main limitations of top-down approach (Hong et al., 2013). Bottom-up approach on the other hand, allows detailed calculations of end-use energy consumption (Swan and Ugursal, 2009). However, it requires robust, detailed and well documented input data for accurate performance (Foliente and Seo, 2012; Wang, 2016). A recent work concluded that, there is a possibility of overestimation of predicted consumption compared to actual consumption due to impact of user behaviour, such as variable heating demands (Novikova et al., 2018). Hybrid models, which are the combination of both top-down and bottom-up approaches, have also been developed to bridge the gap between both approaches (Bohringer and Rutherford, 2008; 2009).

Insert Table 1: A summary of top-down and bottom-up energy benchmarking approaches

2.2 Building classification

To improve the energy performance of a building, it is important to assess as clearly and accurately as possible the actual energy consumption of the building, which would be essential prior to the application of suitable building retrofit measures (Ballarini et al., 2014). However, as the existing building stock is wide, heterogeneous and composed, they should be disaggregated according to different categories, such as, construction type, location and occupancy profile, all of which can have significant effect on the expected energy use of the buildings (Jenkins, 2010) and classified according to similar or common parameters. It is important to carry out energy analysis of the building stock, rather than single buildings (Mauro et al., 2015), where accurate models could be developed to represent building stock for estimating baseline energy consumption in the building sector (Kavgic et al., 2010).

A term 'building typology' can be defined as a systematic classification of buildings according to parameters commonly found (Ballarini et al., 2014). In general, buildings can be classified according to three common criteria, which are climatic zone, construction period or building age, and building size and shape (Ballarini et al., 2017; Caputo et al., 2013). In Italy, residential building typology was defined in TABULA project using these criteria (Ballarini et al., 2017). In the UK, non-domestic and domestic building typologies were defined (TARBASE, 2010) according to their prominence in the building stock as a whole, period of construction and also their relevance to the range of construction methods found in the existing building stock (Jenkins, 2010; Taylor et al., 2010). In sub-tropical or tropical countries where cooling dominates, buildings are also classified according to the types of air-conditioning system used in terms of electricity consumption (Veloso et al., 2017).

Building parameters and architectural variables have been identified as crucial criteria for building classification, which also affect the building energy consumption (Paixão, 2013; Veloso et al., 2017). Ascione et al. (2017) identified 46 characteristic parameters related to geometry, thermal envelope, building operation and type of in-room terminals for space conditioning when classifying office buildings in Italy. Attia et al. (2012) classified residential buildings according to their gross floor areas, building parameters and thermal performance of envelope in Egypt. In addition, building stock can also be categorised based on usage, historical, political and social-economic proceedings in Greece (Theodoridou et al., 2011). In Brazil, income levels were the main criteria to be considered in the development of building typologies in the social housing sector (Triana et al., 2015). Architectural variables and types of air-conditioning systems are critical in office building classification (Veloso et al., 2017). Alves et al. (2017) developed a framework to estimate the energy use intensity (EUI) of an existing building stock based on the combination of land use legislations, land tax database and a field study. In that particular study, three representative typologies were identified for the high-rise commercial building stock in Belo Horizonte, Brazil based on bottom-up archetype energy modelling. They concluded that newer buildings (for example, from the 2000s) can be more energetically intense as high-energy efficiency of individual systems do not necessarily equate to lower energy consumption. Table 2 shows a summary of main criteria used for building classification undertaken by previous researchers.

Insert Table 2: A summary of main classification criteria used for building typology

Among the various methods used to collect data for building classification, physical surveys (e.g. field studies) (Alves et al., 2017; Ballarini and Corrado, 2009), remote survey or mapping (e.g. use of street views of Google Earth to capture building images) (Alves et al., 2017; Pittam et al., 2016), photographic surveys and architectural plans (Pedreira, 2010), all can gather useful physical characteristics of building envelopes for building classification. Field surveys can be useful to obtain geometrical parameters, constructive properties, typological features and system data of the surveyed buildings (Ballarini and Corrado, 2009), as well as identify prevalent building characteristics (Alves et al., 2017). In Brazil, Brandão (2003) and Santana (2006) conducted field surveys to group buildings according to construction parameters. Data from the literature survey can also be used together with field surveys to obtain most representative features in terms of form, materials and construction systems, equipment and operation (Torcellini et al., 2008). The use of remote methods can extract building façade and roof geometrical data virtually, normally using photogrammetric techniques through the use of static panoramic viewpoints from Google Street View and aerial spot images from Google Earth (Alves et al., 2017; Pittam et al., 2016). Cluster analysis is a statistical technique which can be used to find subgroups within a building sample. It has been widely reported in a number of studies related to building classification. For examples, a district clustering modelling approach (Yamaguchi et al., 2007), school building classification (Gaitani et al., 2010), examination of the influences of occupant behaviour on building energy consumption (Yu et al., 2011), estimation of potential energy savings in lighting systems in buildings (Petcharat et al., 2012), understanding of energy savers and influencing factors in Brazil (Giglio et al., 2014), and the division of large samples into more homogeneous and small groups in order to obtain reference buildings (Lara et al., 2015; Schaefer and Ghisi, 2016). To cluster similar characteristics from a building sample, 'Morphological chart' (Pedreira, 2010) or 'Morphological Box' (Alves et al., 2017) can be used.

2.3 Energy analysis of the building stock

EUI is a common feature used previously to represent the energy consumption of a set of uniform buildings within an area and can be expressed as kWh/m^2 per year. EUI can be derived from published standards of typical building consumption patterns, or from auditing energy consumption of a representative sample of buildings, or computed using statistical or physics-based energy models of representative buildings (Choudhary, 2012). As EUI baselines are essential to understand the building stock energy consumption, previous researchers calculated the EUI of the building stock using various methods, such as framework development (Alves et al., 2017), simulation software (Hong et al., 2013; Shabunko et al., 2016) and combined studies of utility bills and construction characteristics (Katafygiotou and Serghides, 2014). In addition to EUI, the average energy use per person (EUP) (kWh/person/year), which was more relevant in the local context, has also been calculated in some studies (Filippin, 2000; Wang, 2016).

The effect of carbon emissions from the built environment on climate change has been recognised globally and analysed in the past (Jing et al., 2017; Ren and Gao, 2010). Various methods have been adopted to calculate the carbon emissions from electricity. For example, carbon intensity (kg/kWh) has been used to calculate carbon emission rate from electricity (Ren and Gao, 2010); whilst the equivalent carbon dioxide emissions (CO_2e) was described by Jing et al. (2017) to measure how much a given building type will produce and the amount of greenhouse gases it may cause. The CO_2e of energy consumed by a building can be estimated by its annual electricity consumption (*n*) multiplied by the emission factor (fCO_2), which can be illustrated in Equation 1.

$CO_2e = n \times fCO_2$ (Eq. 1)

Occupant density is a parameter used in previous studies to investigate the design and ventilation strategies of buildings, which can be expressed as the amount of persons (occupants, users, employees) per m^2. The calculation of occupant density is also crucial in the determination of energy use which directly results from ventilation strategies. Priyadarsini et al. (2009) investigated the correlation between EUI and occupant density in a hotel building. It was concluded that an increase in occupant density has a positive implication on the EUI of a hotel, which directly reflects the level of business activities in the hotel. Thus, occupant density is an important determinant, which may result in the variations of the energy consumption in buildings. In this study, occupant density can be defined as the number of bank employees during main office hours per 100 m^2 of conditioned floor area (person/100 m^2).

3 Method employed in this study

Bank buildings have been selected for this study because they can be commonly found in any typical Brazilian city. A building sample of 72 bank branches has been chosen in the southern Brazilian city of Curitiba, which represents approximately 15% of the total of 480 existing bank branches (Sindicato dos Bancários de Curitiba e Região, 2017). In Brazil, bank buildings are generally subject to a centralised management structure. Therefore, the availability of large quantities of dataset from facilities and engineering teams in the bank makes it easier to pool together data from all branches managed by the bank (Borgstein & Lamberts, 2014).

3.1 Data acquisition

An engineering technique of bottom-up approach was undertaken to investigate building typology and model the energy consumption of bank branches in Curitiba. The technique was developed largely based on the archetypes technique, which bank branches were clustered in different cohorts of similar geometry, size, construction details, and other similar criteria. A bottom-up energy auditing approach was also adopted with three-year (2014 to 2016) electricity bills provided by the bank facilities management and engineering teams. Only electricity consumption was obtained for the bank branches surveyed because non-electric energy use is negligible as central cooking facilities or hot water systems are seldom available (Borgstein and Lamberts, 2014).

3.2 Multi-stage approach

The work presented in this paper is part of a larger study to evaluate the energy efficiency of bank branches in Brazil and their consistency compared with the energy rating calculated using the RTQ-C system, which can be divided into four stages.

Stage 1: Investigation of building parameters

Figure 1 shows the approximate locations of these bank branches in the Metropolitan Area of Curitiba. As all bank buildings are located in a similar climate zone, any influence on the building energy consumption due to differences in climate zone is assumed to be negligible. All bank branches also have a standard working schedule from 8am to 6pm, Monday to Friday. The cash machine facilities are available from 6am to 10pm every day. To retain anonymity of individual bank branches, bank branches have been identified as Building 1, 2 and so on. The dataset from these bank branches were obtained from the bank facilities management and engineering team.

Insert Figure 1: Approximate location mapping of bank branch buildings within Curitiba's Metropolitan Area

Due to the need to deal with a large number of building samples in this study, the use of the remote method of surveying and mapping has been identified as the most appropriate and feasible technique to extract required information, such as building size, shape, orientation, etc. It has the benefit of speeding up the surveying process and generating large-scale building stock geometrical databases remotely. In this study, a virtual tour of the 72 bank branches was carried out using static panoramic viewpoints from Google Street View™ and aerial spot images from Google Earth™ to collect building geometrical data and orientation, which can be used to assist with the development of various typologies for bank branches. Building design data and parameters assessed in the remote survey are orientation of front façade, shape and size of the buildings, number of storeys and shading to external building façade. The building images and their urban context were captured through Street View tool to collect building information and urban parameters.

Stage 2: Classification of bank branches

The archetype bottom-up technique was adopted to classify and cluster the bank branches according to building age, size, type, and other similar characteristics or criteria. Prevalent attributes of the bank branches in each typology were determined and identified, which represent primary features and characteristics in each building typology.

Stage 3: In-depth parametric assessment of selected bank branches

From the original database of building samples, 33 bank branches were selected for a further in-depth assessment, involving studies and analysis of building parameters and designs using architectural and engineering design drawings. The rest of the branches were excluded because detailed design drawings and building plans were unavailable due to: a) the buildings were too old and further design details were unavailable from the bank management and engineering teams; b) not all the buildings in the study are owned by the bank and no further design details could be made available for rented buildings. Geometrical and parametric information from 33 selected branches were collected, such as building shape, construction and design details, type of air-conditioning system, conditioned floor areas, and physical properties of envelope (walls, floors, and windows). The assessment was carried out based on the dataset provided by the bank facilities management and engineering teams, such as architectural drawings and building specifications detailing floor plan designs and physical properties of the branches. In this stage, measurable building parameters and variables calculated are building orientation, external shading devices, window-to-wall ratio (WWR), and U-values. The impact of variables, such as, building orientation and window opening area, which might potentially affect lighting and cooling loads of bank branches are investigated. Visits and in situ inspections were further carried out in 13 of the 33 branches initially surveyed. During the inspections, existing building services and lighting systems as well as detailed construction features were surveyed.

Stage 4: Energy analysis of the bank branches

An energy consumption analysis of the selected bank branches was carried out using key approaches and parameters, such as EUI, occupant density, WWR and carbon emission. The results were later analysed; critical and influential design parameters and characteristics were identified and summarised. Carbon dioxide emissions of the energy consumed by each bank branch can be calculated by multiplying its mean annual electricity consumption from 2014-2016 with the latest (2014) carbon dioxide emission rate (gCO_2 per kWh of electricity) in Brazil (IEA, 2017). This was to ensure a more accurate energy consumption data and energy consumption trend of each bank branch. A significant increment of carbon emission rates from 68.86 (year 2011) to 160.41 (year 2014) gCO_2 per kWh of electricity demonstrates that this issue should be given a serious consideration in the study. Such increment was largely due to increasing electricity demand in Brazil, which has resulted in more electricity to be generated using fossil fuels (Schinazi, 2018). Recent work also predicted the increasing demand of electricity generation using fossil fuels to meet the Brazilian energy demand in future (de Faria and Jaramillo, 2017).

Multiple regression analysis (MRA) were carried out with the buildings' attributes, which allows the determination of which parameters have greater influence on the energy consumption of the bank branches. The influence of a range of independent variables, such as floor area, year of construction, number of occupants, occupant density, orientation of front façade and solar shading/ protection was correlated with the EUI (dependent variable). The ranges of the independent variables used in the MRA are listed in Table 3. These variables were considered as they were the only variables directly obtainable from the bank organisation.

Insert Table 3: Ranges of independent variables and analysis of variance for the MRA

The relationship between the dependent variable and independent variables can be written as Equation 2, where y is a predicted value of the dependent variable (EUI), a is the value of y when all independent variables (x_1, x_2, x_3, ….x_i) are zero and b_i are the coefficients found for each parameter in the formula.

$$y = a + b_1 x_1 + b_2 x_2 + b_3 x_3 + ...b_i x_i \quad \text{(Eq. 2)}$$

A Linear Discriminant Analysis (LDA) was further carried out to identify the most relevant factors which define a low and a medium-high electricity consumer among 13 of the branches surveyed after in situ inspection by the researchers. The inspection focused on the items defined in RTQ-C. The more complete dataset used for LDA had more diversified variables ranging from total percentage of openings relative to wall façades to automatic control of artificial lighting. Each variable has been assigned a given value according to a standardized five-point scale. For example, for percentage of openings, different ranges were established according to the following scheme: 0-20% (value assigned = 1), 21-40% (value assigned = 2), and so on. The definition of low and medium-high was based on the benchmarks for bank branches in Brazil reported by Borgstein and Lamberts (2014). LDA can find a linear combination of features that discriminate between two or more classes of objects or events. IBM SPSS Statistics was used for LDA. Correlations indicate the strength of each influential or discriminating variables and the general classification score of the LDA function.

4 Results and discussion

Amongst the 72 bank branches studied, relevant building information and calculated occupant density and EUI for these branches are investigated. Figure 2 shows the graphical distributions of conditioned floor areas, occupant density and EUI for these branches, with a mean EUI of 134.52 kWh/m^{2}year and a standard deviation of 32.19 kWh/m^{2}year. The minimum discrepancy in energy consumption was probably due to similar types of activities and consistent operating patterns in the branches. Despite the bank branches have a mean area of 975.52 m^2 with a standard deviation of 472.91 m^2, small branches are generally seen to be more common with most branches are below the mean value. The bank branches also have a relatively low and consistent occupancy rate with a mean of 2.75 person/100 m^2 and a standard deviation of 0.80 person/100 m^2.

Insert Figure 2: Distribution of EUI (kWh/m^{2}year), conditioned floor areas (m^2) and occupant densities (person /100 m^2) for all bank branches surveyed

Figure 3 further shows the frequency distribution of EUI, areas and occupant densities in all branches, where more than half of the bank branches have EUI of 150 kWh/m^{2}year or less, average floor area 900 m^2 and occupant densities of between 2 and 3 person/100 m^2. A quick comparison of the EUI with energy benchmarking indicators in Brazil (CBCS, 2017) shows that more than two-thirds of these bank branches are either within the typical range of energy consumption (approximately from 137 to 175 kWh/m^{2}year) or can be considered as energy efficient (approximately less than 137 kWh/m^{2}year) in Brazil.

Insert Figure 3: Frequency distribution of EUI (kWh/m^{2}year), conditioned floor areas (m^2) and occupant densities (person/100 m^2) of the bank branches surveyed

Independent variables detailed in Table 3 were considered to investigate their implication on the energy performance of the bank branches. Using MRA, Eq. 3 had been derived based on Eq. 2 using coefficients obtained from Table 3 to study the individual influence of building parameters (independent variables) on the EUI (dependent variable). The MRA shows R^2, adjusted R^2 and significance F of 0.253, 0.185 and 0.0033, respectively. Due to the low R^2 predicted, the formula expressed in Eq. 3 is subject to further studies and validation using similar building data to increase the reliability.

$$y = 180.83 - 0.11 \times x_1 + 1.59 \times x_2 + 3.49 \times x_3 - 18.44 \times x_4 + 1.91 \times x_5 + 8.78 \times x_6 \quad \text{(Eq. 3)}$$

4.1 Bank typologies

Similar building parameters and characteristics were clustered from the 72 bank branches and classified into four typologies shown in Figure 4, according to common shapes, sizes and geographical layout of the buildings. Despite the fact that some building shapes are irregular, most bank branches have a common rectangular shape, which is consistent with previous findings (Alves et al., 2017). Type A bank branches can be defined as bank branches located inside a larger building complex, normally situated city centre, such as, high-rise buildings used for both residential and commercial activities, university buildings, and shopping malls. Access to Type A bank branches can be either from the external façade or from within the buildings. Type B refers to bank branches in terrace buildings, which are usually low-rise with both sides of the external façade attached to adjacent buildings and normally located in populated urban areas. Bank branches normally occupy part of the buildings, which are also used for other business activities, such as stores and restaurants. Type C bank branches are located in semi-detached or end of terrace buildings, which are mostly low-rise with one side of the façade attached to adjacent buildings in less populated suburban areas. Type D bank branches are detached and free-standing, which are mostly low-rise and located in suburban areas. Both Type C and Type D bank branches have more open spaces adjacent to the buildings, which could be converted into parking spaces.

Insert Figure 4: Different typologies of bank branches in Curitiba

Table 4 shows the analysis of building characteristics, energy consumption and carbon dioxide emissions for different bank typologies. Type A branches have the largest mean conditioned floor area of 1097.02 m^2 due to the generally larger bank branches located in the city centre, which are primary branches with higher staff occupancy and frequently visited by customers. Types C and D branches are more prevalent as they are widely available in the entire urban and suburban areas of Curitiba. These types of branches are mostly located in less congested areas with parking spaces available. Type A bank branches have the largest deviation in the EUI (47.78 kWh/m^2year), compared with the rest of the branches because the branches are mostly located within other larger building complexes with variable degree of energy efficiency.

Insert Table 4: Summary of characteristics and energy consumption of all types of bank branches

The detailed analysis of the bank branch stock according to their age is shown in Table 5. More than 58% of the bank branches were constructed in the 2010s, which shows a significant expansion in the amount of bank branches since then. Modern bank branches are more compact in building size (mean area of 821.99

m^2) compared with pre-2000 bank branches (1504.71 m^2). Post-2010 bank branches also have smaller occupancy rates compared to other types of bank branches for providing more comfort to occupants. Most of the bank branches that are constructed post 2000s are Type C and D branches and spread over a wider urban area, which is a sign of economic growth and expansion of Curitiba's Metropolitan Area in the last 15 years.

Insert Table 5: Summary of characteristics and energy consumption of bank branches according to building age

The EUI analysis shows that post-2010s bank branches, which are newer, modern, and usually considered as more energy efficient and sustainable are not always the case. The post-2010s bank branches are in fact among the largest consumers of energy with higher EUI. This demonstrates that buildings equipped with newer and higher energy efficient systems do not usually have lower energy consumption, a conclusion which is supported by a previous energy study on Brazilian commercial buildings (Alves et al., 2017).

4.2 Analysis of building services, design parameters and critical influential factors

From the in-depth analysis of architectural drawings, generic types of available air conditioning systems, wall thicknesses, wall and window areas could only be identified and measured for 33 out of 72 bank branches. Among the 33 branches, 73% use a hybrid type of air conditioning system, which consist of a combination of multi-zone (multi-split) and window unit (split). This is most common because most bank branches have complex internal floor layouts with a mixture of common public spaces for banking transaction and private office floors for administrative work, which require different types of air conditioning systems. Other branches use either central, multi-split or chiller types of air conditioning systems. Apart from the multi-split systems which are most commonly used in Type A bank branches, hybrid air conditioning systems are prevalent in all other types of bank branches as shown in Table 6. Bank branches with hybrid systems have higher EUI (137.06 kWh/m^2year) than the branches with multi-split systems alone (118.4 kWh/m^2year).

Insert Table 6: Key attributes of the building envelope and physics according to bank typologies for 32 selected bank branches

All bank branches have brick wall thicknesses of between 15 and 20 cm, which are typical for Brazilian buildings, with U-values ranging from 1.85 to 2.46 W/m^2K according to RTQ-C regulations (MME, 2013). In terms of WWR, glazing areas account for approximately 54% of the front façades of all bank branches, in which westerly orientation prevails. For sunlight optimization, north and west façades of all bank branches have the largest glazing areas (42.47% and 38.32%, respectively). Nearly half of the bank branches have external shading devices, such as overhangs, for solar protection during summer months, due to large glazing areas at the north and west building façade.

The study was consistent with the findings from Borgstein and Lamberts (2014) in two ways. Firstly, more than two-thirds of the bank branches in Curitiba have energy consumption of between 137 and 175 $kWh/m^2/year$, which is consistent with the mean (180 $kWh/m^2/year$) presented by Borgstein and Lamberts (2014). Secondly, building-specific variations did not sufficiently explain energy consumption in both studies. Borgstein and Lamberts (2014) further found a "climate correction factor" to be important when accounting for bank branches in different climate zones.

The LDA was further used to allow the identification and rank of variables which define low and medium-high consumers. Table 7 shows the relations of up to 20 variables as correlations between discriminating variables and standardized canonical discriminant functions. Table 8 shows general LDA classification score. The most influential variables are total percentage of openings and occupant density. LDA yielded the correct classification (92.3%) of original grouped cases.

Insert Table 7: Structure Matrix - Pooled within-group correlations between discriminating variables and standardized canonical discriminant functions – Variables ordered by absolute size of correlation within function

Insert Table 8: LDA Classification results

5 Conclusions

Previous studies concluded that, lack of building energy benchmark studies makes it difficult to understand the energy demand of building stock in Brazil. This paper presents a methodology, which involves multi-stage approach to systematically identify the typologies of bank buildings in Curitiba, Brazil and investigate the effects of different available parameters using MRA and LDA progressively. The method proposed to study the energy performance of bank branches has adopted an archetype bottom-up technique, using a combination of various studies, such as, EUI, building classification, MRA, and LDA. The defined bank typologies provide insight into a better understanding of the design characteristics and their energy consumption of bank branches in Curitiba, which can form the basis for future bank building classification in Brazil. Despite the fact that very small correlations were found between energy consumption (EUI) and variables (R^2 of 0.253), such as occupant density, conditioned floor areas, WWR, and façade orientation, among other aspects, LDA shows that a few parameters stand out for differentiating between low and medium-high consumers. The sequence of the research methods adopted in this study has been particularly useful for building classification and energy analysis of large and complex building stock. In the absence of complete building parameters, the multi-stage approach has been used to identify useful and critical design parameters with the aid of MRA and LDA. This approach can be adopted by other similar building stock with greater complexity in other cities.

This study does not include energy modelling of selected bank branches within each typology using detailed building service systems and building variables. The modelling could be conducted using RTQ-C system based on a sample bottom-up technique utilising a dataset of selected actual bank branches as input information. The calculated energy ratings could then be used to compare with the actual energy consumption data, which will be the subject of future work. It is recommended that a detailed breakdown of energy consumption within bank branches should also be the subject of future work to give a better understanding on the major energy consumers within the buildings. It would provide crucial and useful to generate a dataset for energy benchmarking and implementation of energy efficient measures. An effective method of creating such a dataset should be developed and identified, which can provide essential knowledge among building interaction and insights into energy saving opportunities of the existing building stock.

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Nomenclature

Acronyms

EPBD	Energy Performance of Building Directives
EU	European Union

EUI	Energy use intensity
EUP	Energy use per person
HVAC	Heating, Ventilation and Air-conditioning
CFA	Conditioned floor area
LDA	Linear Discriminant Analysis
MRA	Multiple Regression Analysis
PROCEL	Brazil's National Electricity Conservation Programme
RTQ-C	The Energy Efficiency Rating - Technical Quality Regulations for Commercial, Service and Public Buildings
US	United States
UK	United Kingdom
WWR	Window-to-wall ratio

Symbols

a	Intercept
b_i	Coefficient
e	Equivalent
f	Emission factor
n	Annual electricity consumption
R^2	Multiple correlation coefficient
x	Independent variable (factor)

y Dependent variable

Chemical symbols

CO_2 Carbon dioxide

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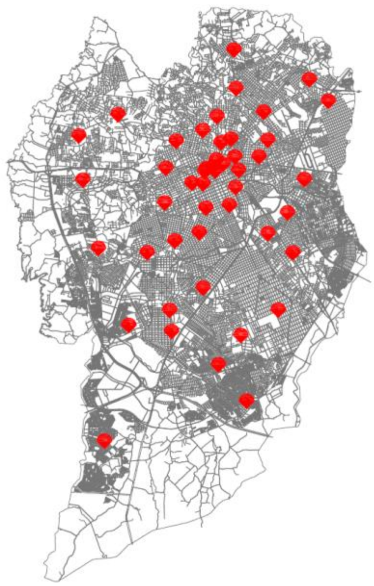

Figure 1: Approximate location mapping of bank branch buildings within Curitiba’s Metropolitan Area

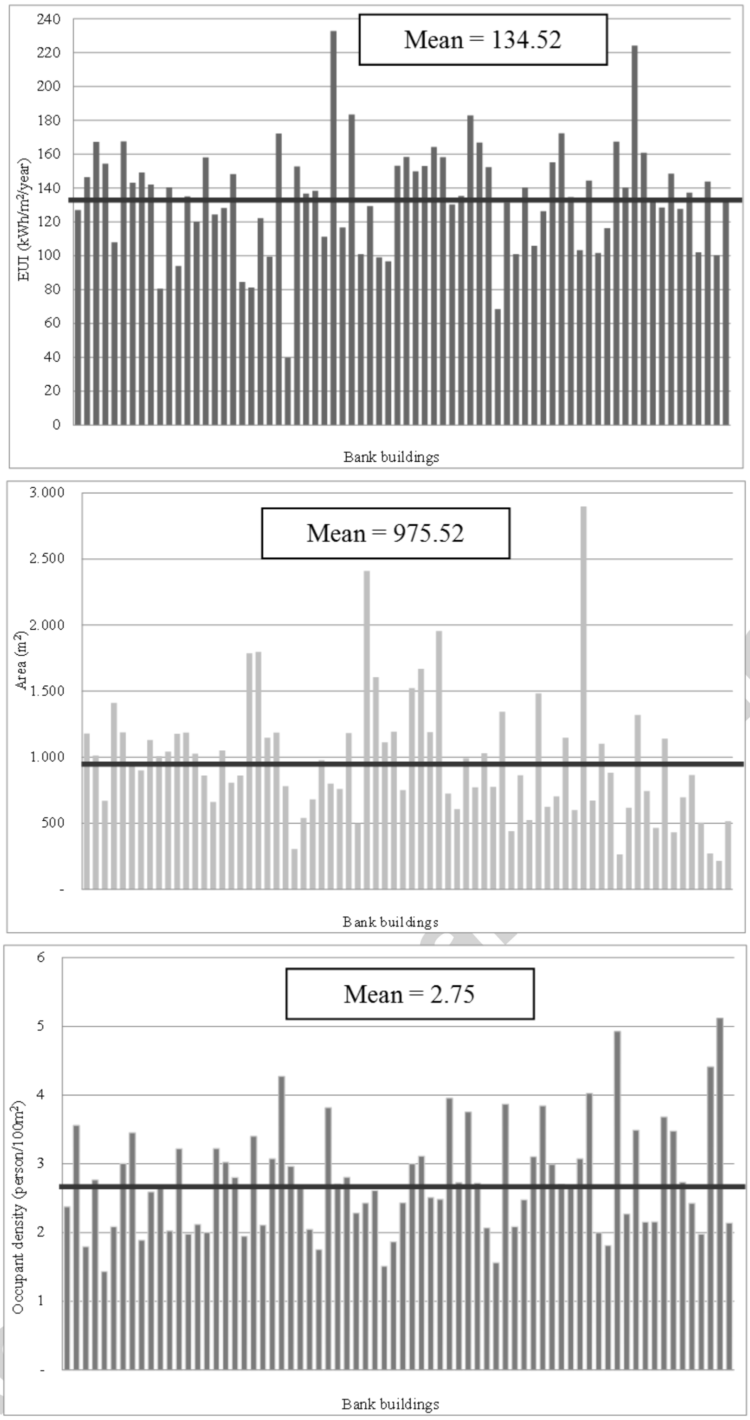

Figure 2: Distribution of Energy Use Intensities (EUI) (kWh/m^2year), internal floor areas (m^2) and occupant densities (person /$100m^2$) for all bank branches surveyed

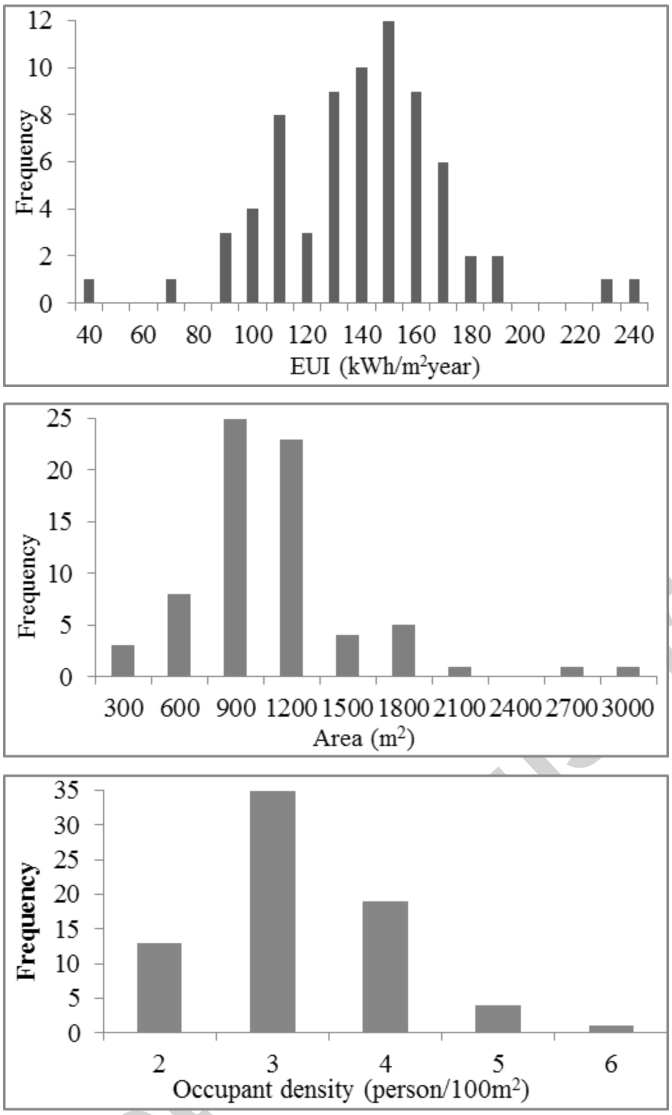

Figure 3: Frequency distribution of Energy Use Intensities (EUI) (kWh/m^{2}year), internal floor areas (m^2) and occupant densities (person/100m^2) of bank branches

Types	Descriptions	Examples of building images	Common building features
A	A branch in a building complex		• Low-rise (not more than three floors) or high-rise (more than three floors) • Located in a high-rise building (occupying lower floors for banking services or higher floors for offices) or large building complex (e.g. shopping centre or other institution) • Located in both downtown and sub-urban areas • Mostly rectangular shape
B	Terrace		• Attached to adjacent buildings on both sides • Low-rise (not more than three floors) • Mostly located in densely populated downtown area • Mostly rectangular shape
C	Semi-detached/ end-terrace		• Attached to adjacent building on one side • Low-rise (not more than three floor) • Mostly located in sub-urban areas with less obstruction/ shading from adjacent buildings • Mostly rectangular shape
D	Detached/ stand-alone		• Low-rise (not more than three floor) • Detached from adjacent buildings on all sides • Mostly located in sub-urban areas with less obstruction/ shading from adjacent buildings • Mostly rectangular shape

Figure 4: Different typologies of bank branches in Curitiba

Characteristics	Top-down	Bottom-up
How is energy calculated?	Aggregate (Heiple and Sailor, 2008)	Disaggregate or hourly (Heiple and Sailor, 2008)
Level of input data	• Macroscopic (Heiple and Sailor, 2008) • National energy statistics (Bohringer and Rutherford, 2008; Grandjean et al., 2012; Jones et al., 2015; Theodoridou et al., 2011)	• Microscopic • Specific building context (Burman et al., 2014)
Calculation technique	Downscaling (Swan and Ugursal, 2009)	Scaling up (Swan and Ugursal, 2009)
Modelling	Broader economy (Bohringer and Rutherford, 2008; 2009)	Energy system at building level (Bohringer and Rutherford, 2008; 2009)
Variables/ data available	• Appliance efficiency, energy price, weather conditions (Sousa et al., 2017) • Historical energy consumption data, polluting emissions (Mauro et al., 2015) • Carbon dioxide emission data, national energy statistics (Kavgic et al., 2010) • Gross domestic product, population figures (McLoughlin et al., 2012) • Employment rates (Swan and Ugursal, 2009) • Market prices (Grandjean et al., 2012) • Housing statistics or economic data (Mastrucci et al., 2014)	• Building fabric, services and occupancy data (Hong et al., 2013) • Data from representative buildings to represent the large scale at national level (Alves et al., 2017; Foliente and Seo, 2012; Mauro et al., 2015) • Internal conditions, building properties, electricity bills and end-use data or energy consumption of appliances (Grandjean et al., 2012; Sousa et al., 2017) • Appliance power ratings or end-use characteristics, such as, geometry, envelope fabric, equipment and appliances (McLoughlin et al., 2012; Swan and Ugursal, 2009) • Building characteristics, household composition and occupant behaviour (Mastrucci et al., 2014)

Examples	• Econometric, technological models (Kavgic et al., 2010)
	• Descriptive statistics and artificial neural networks (ANNs) (Hong et al., 2013)
		• Statistical or aggregated end-use
		  • Statistical techniques to attribute historical energy consumption (Mastrucci et al., 2014)
		  • Data-driven (Alves et al., 2017)
		  • Regression analysis, conditional demand analysis and ANNs (Swan and Ugursal, 2009; Mastrucci et al., 2014)
		  • Energy audit (Borgstein and Lamberts, 2014)
		  • Bottom-up calculation models (REMA) (Tuominen et al., 2014)
		  • GIS based statistical methodology (Mastrucci et al., 2014)
		• Physical or engineering-based
		  • Three types: distribution, archetypes and sample (Swan

		and Ugursal, 2009) • Simplified analytical models (Sousa et al., 2017) • Energy simulation (Tereci et al., 2013)
Benefits	• Simplicity of the aggregated data (Swan and Ugursal, 2009) • Option when data availability is limited (Heeren et al., 2013)	• Consider occupant behaviours (Mastrucci et al., 2014; Swan and Ugursal, 2009) • Estimate building energy consumption through mathematical equations (McLoughlin et al., 2012; Swan and Ugursal, 2009) • Determine end-use energy consumption and identify energy-saving measures (Swan and Ugursal, 2009) • Model technological options and predict energy savings (Mastrucci et al., 2014) • Determine the impact of energy efficiency measures of buildings (Mata et al., 2013; Mastrucci et al., 2014) • Use of specification of lower level system to build up a more precise overview (Hong et al., 2013)
Limitations	• Low granularity of data and accuracy of the methods (Hong et al., 2013) • Unable to investigate the impact of specific measures or technologies (Heeren et al., 2013)	• Reliance on knowledge from building physics (Alves et al., 2017) • Reliance on quantitative data on building characteristics (Mastrucci et al., 2014) • Reliance on robust, detailed and well documented data (Foliente and Seo, 2012; Wang, 2016) • Based on prototypical buildings with limited comparison against measured data (Mastrucci et al., 2014) • Overestimation of predicted consumption compared to actual consumption due to impact of user behaviour (Novikova et al., 2018)

Table 1: A summary of top-down and bottom-up energy benchmarking approaches

References	Geometry	Climatic zone	Age	Thermal performance	Usage	HVAC
Alves et al. (2017)	■	■	■	■	■	■
Ascione et al. (2017)	■			■	■	■
Attia et al. (2012)	■			■		
Ballarini & Corrado (2009)			■	■	■	
Ballarini et al. (2014)			■	■		■
Ballarini et al. (2017)	■	■	■			
Caputo et al. (2013)	■		■			
Katafygiotou & Serghides (2014)	■	■	■	■		■
Mastrucci et al. (2014)	■		■			
Spyropoulos & Balaras (2011)	■					
Theodoridou et al. (2011)	■	■	■	■	■	■
Tereci et al. (2013)	■		■	■		
Veloso et al. (2017)						■

Table 2: A summary of main classification criteria used for building typology

Independent variables (unit)	Range of variation	Coefficients	p-values
x_1 - Area (m^2)	215.05 to 2897.65	-0.11	0.0012
x_2 - Year of construction (year)	1980 to 2015	1.59	0.7938
x_3 - Number of occupants (person)	10 to 89	3.49	0.0024
x_4 - Occupant density (person/100m^2)	19.55 to 69.91	-18.44	0.0463
x_5 - Orientation of front façade	east (1), west (2), south (3) and north (4)	1.91	0.5588
x_6 - Solar shading/ protection	yes (1) and no (2)	8.78	0.1304

Table 3: Ranges of independent variables and analysis of variance for the MRA

Descriptions	All	Type A	Type B	Type C	Type D
N (sample size)	72	12	15	25	19
Conditioned floor area (m^2)					
-Mean	975.52	1097.02	997.55	920.70	977.77
-Standard deviation	472.91	586.73	411.07	551.71	329.01
Mean construction year	2008	2007	2005	2009	2008
Mean occupancy					
-Number of employees	25.78	29.50	28.40	25.12	23.00
-Occupant Density(person/100m^2)	2.75	2.88	2.88	2.82	2.49
EUI (kWh/m^2 per year)					
-Minimum	39.76	39.76	84.52	98.99	68.47
-Maximum	232.76	232.76	182.93	224.07	183.50
-Mean	134.52	134.68	132.60	133.07	137.85
-Standard deviation	32.19	47.78	27.33	26.19	34.32
CO_2 emission (kgCO_2/year)					
-Total	1,481,458	282,174	313,518	486,347	388,364
-Mean	20,576	23,514	20,901	19,454	20,440

Table 4: Summary of characteristics and energy performance of all types of bank branches

Descriptions	Pre-2000	2000 to 2009	Post-2010
N (sample size)	8	22	42
Prevalent branch typology	B (50%)	C & D (64%)	C (39%)
Mean internal floor area (m^2)	1504.71	1076.17	821.99
Mean occupancy (persons)	44	29	20.55
Mean occupant density (person/100m^2)	3.02	2.88	2.63
EUI (kWh/m^2year)			
-Mean	129.11	135.55	135.00

Table 5: Summary of characteristics and energy performance of bank branches according to building age

Descriptions	All	Type A	Type B	Type C	Type D
N (sample size)	32	4	5	12	11
Front façade orientation	West	West	West	West	No prevalent orientation
Mean WWR (%)					
- Front	54.09	69.12	57.61	39.99	49.62
- North	42.47	85.71	21.93	30.25	31.97
- South	34.92	44.50	21.63	46.81	26.74
- West	38.32	20.53	60.93	38.59	33.21
- East	27.91	52.54	25.32	16.13	17.64
External wall					
- Type	brickwork	brickwork	brickwork	brickwork	brickwork
- Thickness (cm)	15-20	15-20	15-20	15-20	15-20
- U-value (W/m^2K)	2.46-1.85	2.46-1.85	2.46-1.85	2.46-1.85	2.46-1.85
Air conditioning system					
- Hybrid	73%	33%	80%	64%	100%
- Others	27%	67%	20%	36%	0%
External shading					
- Branches with external shading device	48%	50%	40%	45%	55%

Table 6: Key attributes of the building envelope and physics according to bank typologies for 32 selected bank branches

Variable	Function
Percentage of openings	-.572
Occupant density	.542
Percentage of openings (west façade)	-.339
Shading devices	.325
Year of construction	-.325
Percentage of openings (east façade)	.293
Air-conditioning equipment	-.287
Percentage of openings (north façade)	-.287
Percentage of openings (front façades)	.249
Connection to ground (underground parking)	-.243
Thickness of duct insulation	-.217
Built area	.137
Percentage of openings (south façade)	.122
Orientation of front façade	.099
Typology	.089
Electric circuits	-.071
Thermal transmittance (roof)	-.071
Thermal transmittance (wall)	-.071
Number of floors	-.039
Lighting system (automated control)	.030

Table 7: Structure Matrix - Pooled within-group correlations between discriminating variables and standardized canonical discriminant functions – Variables ordered by absolute size of correlation within function

		Consumption		Predicted Group Membership		Total
				low	medium-high	
Original	Count	Groups	Low	3	0	3
			medium-high	1	9	10
	%	Groups	Low	100	0	100
			medium-high	10	90	100

Table 8: LDA Classification results

Highlights:

- A multi-stage approach was performed to analyse dataset of 72 bank branches
- A bottom-up techniques was performed to classify bank branches
- Post-2010s bank branches are among the largest consumers of energy
- Direct correlation was found between energy consumption (EUI) and building parameters